ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/28576506

A study of digital camera colorimetric characterization based on polynomial modeling

Article *in* Color Research & Application · February 2001

DOI: 10.1002/1520-6378(200102)26:1<76::AID-COL8>3.0.CO;2-3 · Source: OAI

CITATIONS
333

READS
1,035

3 authors, including:

Ming Ronnier Luo
Zhejiang University
783 PUBLICATIONS **9,297** CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Image quality evaluation View project

Accurate method for computing correlated color temperature View project

All content following this page was uploaded by Ming Ronnier Luo on 06 December 2018.

The user has requested enhancement of the downloaded file.

A Study of Digital Camera Colorimetric Characterization Based on Polynomial Modeling

Guowei Hong,* M. Ronnier Luo, Peter A. Rhodes

Colour & Imaging Institute, University of Derby, Derby DE22 3HL, United Kingdom

Received 24 August 1999; revised 21 February 2000; accepted 30 June 2000

Abstract: The digital camera is a powerful tool to capture images for use in image processing and colour communication. However, the RGB signals generated by a digital camera are device-dependent, i.e., different digital cameras produce different RGB responses for the same scene. Furthermore, they are not colorimetric, i.e., the output RGB signals do not directly correspond to the device-independent tristimulus values based on the CIE standard colorimetric observer. One approach for deriving a colorimetric mapping between camera RGB signals and CIE tristimulus values uses polynomial modeling and is described here. The least squares fitting technique was used to derive the coefficients of 3 × n polynomial transfer matrices, yielding a modeling accuracy typically averaging 1 ΔE units in CMC(1:1) when a 3 × 11 matrix is used. Experiments were carried out to investigate the repeatability of the digitizing system, characterization performance when different polynomials were used, modeling accuracy when 8-bit and 12-bit RGB data were used for characterization, and the number of reference samples needed to achieve a reasonable degree of modeling accuracy. Choice of characterization target and media and their effect on metamerism have been examined. It is demonstrated that a model is dependent upon both media and colorant, and applying a model to other media/colorants can lead to serious eye–camera metamerism problems. © 2001 John Wiley & Sons, Inc. Col Res Appl, 26, 76–84, 2001

Key words: camera characterization; camera calibration; device characterization; colour management

*Correspondence to: Dr. Guowei Hong, Colour and Imaging Institute, University of Derby, Kingsway House, Kingsway, Derby DE22 3HL, UK (e-mail: g.hong@derby.ac.uk)

© 2001 John Wiley & Sons, Inc.

INTRODUCTION

With the rapid development of digital computers and image processing techniques, images in digital form are becoming increasingly popular for viewing, transmitting, and printing. They offer many distinct advantages, such as processing flexibility, reliable transmission, ease of storage and retrieval, ease of reproduction, as well as compatibility with digital networks and digital computers.

The digital colour camera is a powerful tool for image acquisition for use in image processing and colour communications. It is especially appropriate, when the scene to be imaged is heavily textured or has a three-dimensional nature. However, accurate handling of the colour characteristics of digital images is a nontrivial task, due to the fact that RGB signals generated by a digital camera are device dependent, i.e., different digital cameras produce different RGB signals for the same scene. Furthermore, the response is not colorimetric, i.e., the resulting RGB values are not a linear transform from device-independent tristimulus values based on CIE colour-matching functions. The reason is that the spectral sensitivity of colour sensors used in digital cameras does not correspond to the device-independent tristimulus values based on the CIE colour-matching functions.[1] Besides, the spectral sensitivity of the sensors used in different cameras varies largely from one another. Therefore, a transform that defines a mapping between camera RGB signals and a device-independent colour space, such as *XYZ* or CIELAB, is essential for high-fidelity colour reproduction. The transform derivation process is known as camera characterization.

With the above in mind, The International Organization for Standardization (ISO) is actively seeking to develop a standard for digital still camera colour characterization. An ISO draft working standard[2] (ISO 17321) has been produced by a joint working group between Technical Committees ISO/TC42/WG18, Photography, and ISO/TC130/

WG3, Graphic Technology. However, it is mainly for camera manufacturers and testing laboratories, not for ordinary users, because the standard requires sophisticated and expensive equipment and unrendered camera data.

Colour characterization methods can be divided into two general categories: (a) spectral sensitivity based and (b) colour target based. With spectral sensitivity-based characterization,[3] the camera spectral sensitivity needs to be measured using specialized apparatus (a monochromator and a radiance meter). A relationship needs to be found between the camera spectral sensitivity and the CIE colour-matching functions. This relationship can then be used to transform camera R, G, B values to *X*, *Y*, *Z* values. The basic idea of colour target-based characterization is to use a reference target that contains a certain number of colour samples. These colour samples are then imaged by a digital camera and measured by a spectrophotometer to obtain the RGB values and their corresponding *XYZ* values. Typical methods like three-dimensional lookup tables with interpolation and extrapolation,[4,5] least squares polynomial modeling,[6] and neural networks[7] can be used to derive a transformation between camera RGB values and *XYZ* values. In this study, the colour target-based approach was used, because this requires only a known target and is, therefore, a more practical method. Polynomial regression was adopted for model derivation. Although a similar technique has been used by Kang[6] for characterizing scanners, there is no research publication for using this method for digital cameras. The main difference between digital cameras and scanners is that scanners have their own fixed illumination, whereas lighting needs to be provided for digital cameras. Although fixed illumination on the scanner might provide more consistent and uniform lighting, a particular choice of certain illumination might be able to optimize characterization performance.

Experiments were carried out to investigate the following:

1. The repeatability of the digitizing system;
2. The characterization performance when different polynomials were used;
3. The difference in modeling accuracy between using 8-bit or 12-bit RGB data for characterization;
4. The number of reference samples required for a reasonable degree of modeling accuracy;
5. The eye–camera (observer) metamerism effect, due to the fact that the spectral responses of the camera sensors are different from colour-matching functions of the CIE standard colorimetric observer.

EQUIPMENT USED

An Agfa digital StudioCam was used. It is a 3 × 12-bit colour digital camera with a resolution of 4500 × 3648 pixels for 36 × 29 mm^2 area. The digital data generated is directly transferred to a computer via a SCSI interface. Lens aperture and focusing are manually operated; the rest of the scanning process is controlled via Agfa's FotoLook software, which operates as a plug-in module for Adobe PhotoShop. The sensors inside the scanning engine are tri-linear colour CCD containing 3 × 3648 elements. The exposure time can be set automatically or manually for a given aperture. In our experiments, the camera RGB values for each colour patch were calculated by averaging RGB values of 90% of the pixels in the patch, excluding those boundary pixels.

The colorimetric data of the reference target were measured using an X-Rite 938 spectrodensitometer. This instrument measures spectral reflectance from 400–700 nm in 20 nm intervals. The light source is a gas-filled tungsten lamp with a filter corrected to approximate the D65 Illuminant. It has a 0/45 illuminating/viewing geometry, and features a dual-beam, single light-pulse compensation method to improve accuracy. The colorimetric data for colour samples on the reference target were calculated under CIE 1931 standard colorimetric observer and Illuminant D50. The *XYZ* values for each colour patch were taken by averaging three measurements from a spectrophotometer. Three measurements were carried out at the same time, but at different positions in the patch.

Two reference targets made of different material were used: an ANSI IT8.7/2[8] (IT8) chart on Kodak Ektacolour Professional Paper and the textile samples selected from The Professional Colour Communicator[9] (PCC) using reactive dyes on cotton. All colour samples on both IT8 and PCC are more or less evenly spaced throughout the full colour gamut of the particular material on which the target has been produced.

The ANSI IT8.7/2 chart provides 264 colour samples, which cover a large colour gamut in CIELAB colour space. The colour samples on the chart can be divided into four sections:

1. A 24-step gray scale.
2. 12 colour samples of skin tones.
3. Series of single dye scales (cyan, magenta, and yellow) with equivalent two and three dye combinations (red, green, blue, and black).
4. The remaining colours consist of 12 samples at each of 12 hues. At each hue angle, three levels of lightness are selected and four levels of chroma are defined at each level of lightness, the outermost being the highest chroma that can be achieved by the dye set used for a particular paper.

The PCC is a loose-leaf file containing 40 pages of small cuttings of dyed cotton arranged according to changing lightness, hue, and chroma. It is based on an approximate CMC(1:1)[10] uniform colour space under CIE Illuminant D65 and 1964 standard observer. Colour samples are arranged using lightness against chroma axes with constant hue angle. Forty hue angles with a 9° interval are used, and each adjacent pair of samples has a 5-unit interval either in the lightness or chroma axis. This produces a population of 2095 colour samples.

TABLE I. Lighting intensities recorded over a period of 4 hours.

Time	0:30	1:00	1:30	2:00	2:30	3:00	3:30	4:00	4:30
L^*	53.53	53.49	53.48	53.34	53.26	53.26	53.25	53.22	53.22

IMAGE CAPTURE SETUP

The setup of the digital camera and its illumination and viewing environment is critical for image acquisition, so that the camera can deliver meaningful and repeatable data. This usually includes illuminant, camera exposure, and compensation for the nonuniformity of the camera lens. Furthermore, the reproducibility of the digitizing system and the uniformity of the sensors must be known.

Illuminant setup, which consists of uniformity and geometry, is of key importance to camera characterization. The lighting illuminating the reference target needs to be as uniform as possible. It is obvious that, if the illumination of each colour patch of the reference target is not uniform, the camera responses of a particular colour patch will vary according to its position. In this study, uniformity was investigated using a photometer. The lighting was carefully arranged so that any area within the picture frame has the same reading from the photometer. Illumination and viewing geometry can affect perceived colour significantly.[11] In our experiment, two lamps (placed about 1 m away from the object being imaged) were mounted on each side of a copy stand. The viewing/illuminating geometry was about 0/45.

The combination of lens aperture size and exposure time determines the amount of light reaching the camera's CCD sensors. Obviously, the signals generated by CCD sensors vary, if the amount of light reaching CCD sensors is different. Therefore, both aperture size and exposure time were fixed during the period of image acquisition. Special attention was paid to setting the exposure to avoid any "colour clipping," i.e., the saturation of one or more of the three RGB channels.

A camera lens does not uniformly transmit light across its area; the center area usually transmits more light. As a consequence, the center pixels appear to be much brighter than those corner pixels when a uniform gray surface is pictured. According to the experimental results obtained, when a uniform mid-gray matt surface was digitized, the RGB values of corner pixels are about 25% less than the center pixels. Therefore, if a picture taken occupies the full frame of the camera, a compensation scheme is necessary for those pixels where lightness levels turn out to be darker.

To check the repeatability of the image capturing system, a uniform gray surface was pictured every 30 min for a 4-h period. The lights were turned on for 30 min to stabilize before taking the first picture. Using a 3×11 matrix derived by the characterization process described later, the original RGB values were first transformed to XYZ values and then to CIELAB values. Table I shows the average L^* values recorded during this period. It can be noted that the lightness values decrease gradually as time goes on. The standard deviation of lightness value, L^*, is 0.13, which is about 0.2% of the mean value. The difference between the beginning and the end of this 4-h period is 0.31. This level of consistency is acceptable and also indicates that the lighting is stable and the imaging system repeatable.

Because the scanning engine inside the camera contains only one array of tri-linear colour CCDs, the uniformity of camera sensors was examined by line-scanning a number of NCS neutral colours on A4-size semi-glossy paper. The lightness L^* values of these samples were ranged from 15–90. Ideally, for each colour sample all pixels on a single line should have the same value for each R, G, B channel. In practice, this is not the case, due to a number of varying factors such as the uniformity of the colour patches, the uniformity of the lighting, camera CCD variations, and quantization errors.

The present results show an overall combination of all these parameters having one effect on the uniformity of the sensor responses. Camera RGB values were transformed to XYZ values using a 3×11 matrix derived by the characterization process described later. The averaged XYZ value of all pixels in a single line was calculated and considered as the standard. Each pixel's variation from the standard was calculated using the CMC(1:1) colour-difference formula. In this study, the CMC(1:1) colour-difference formula was adopted for calculating all the colour differences. The averaged colour difference between each individual pixel and the mean tristimulus values was used as a measure to investigate the agreement among camera CCD sensors. For the particular setup used here, the results show that the average colour differences become significant as the lightness values decreases (see Fig. 1). This clearly shows that the effect of nonuniformity of CCD sensors becomes worse when the lightness level of the object imaged decreases, i.e., the signal-to-noise ratio decreases. This was also partly contributed by the glossiness included in the samples studied. The darker glossy samples were expected to have large variations. However, the effect of nonuniformity was

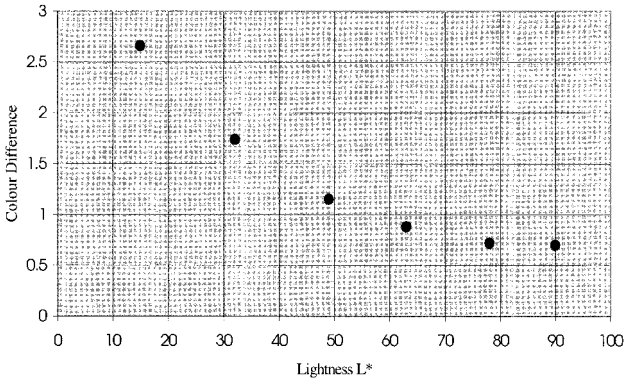

FIG. 1. Uniformity check for CCD sensor responses.

largely reduced when the average RGB values for each colour patch are used for characterization.

POLYNOMIAL REGRESSION WITH LEAST SQUARES FITTING

Device characterization by polynomial regression with least squares fitting has been adequately explained by many other researchers.[12,13] Therefore, only a brief description is given here. Suppose that the reference target has N colour samples. For each colour sample, the corresponding camera response r, g, b can be represented by a 1×3 vector ρ_i ($i = 1 \ldots N$), and their corresponding XYZ tristimulus values can be represented by a 1×3 vector x_i ($i = 1 \ldots N$). If only r, g, b values are used in ρ_i, the transformation between RGB and XYZ is a simple linear transform. The idea behind using polynomials is that vector ρ_i can be expanded by adding more terms (e.g., r^2, g^2, b^2, etc.), so that better results can be achieved. In this study, the following polynomials were studied:

1. $\rho_i = [r\ g\ b]$
2. $\rho_i = [r\ g\ b\ rgb\ 1]$
3. $\rho_i = [r\ g\ b\ rg\ rb\ gb]$
4. $\rho_i = [r\ g\ b\ rg\ rb\ gb\ rgb\ 1]$
5. $\rho_i = [r\ g\ b\ rg\ rb\ gb\ r^2\ g^2\ b^2]$
6. $\rho_i = [r\ g\ b\ rg\ rb\ gb\ r^2\ g^2\ b^2\ rgb\ 1]$.

Let $\mathbf{R}$ denote an $N \times 3$ matrix of vectors ρ_i and $\mathbf{H}$ the corresponding matrix of vectors x_i. The mapping from RGB to XYZ can be represented by

$$\mathbf{H} = \mathbf{MR}, \tag{1}$$

where $\mathbf{M}$ is the unknown transformation matrix sought. Of course, the size of matrix $\mathbf{M}$ changes from 3×3 up to 3×11 depending on the polynomial being solved. The best $\mathbf{M}$ should be defined as the one that minimizes the colour differences over all colour samples. This requires a uniform colour space and a colour-difference formula that correctly represents perceived colour differences. Unfortunately, the XYZ colour space does not meet these requirements. A relatively uniform colour space (such as CIELAB or CMC) would be preferred. However, the mathematics involved is complicated due to their nonlinearity. Thus, for mathematical simplicity, least squares fitting to the XYZ colour space is adopted. This equates to the minimizing of

$$E = \sum_{i=1}^{N} (x_i^T - M\rho_i^T)^2 . \tag{2}$$

The least-squares solution for minimizing E is

$$\mathbf{M} = (\mathbf{R}^T\mathbf{R})^{-1}\mathbf{R}^T\mathbf{H}, \tag{3}$$

where $\mathbf{R}^T$ denotes the transpose of $\mathbf{R}$, and $\mathbf{R}^{-1}$ the inverse. In theory, there is no limit to the order and the number of terms of the polynomial; in practice, it is constrained by the accuracy required, the computational cost, and the number of samples available. Note that the current draft of ISO 17321 adopts a 3×3 matrix using the root-mean square error as a measure of fit. However, their RGB values were initially linearized based on ISO RGB colour-matching functions. The method used in this study is considered to be a lot simpler in terms of computation than to that in ISO 17321.

Two experiments were carried out to investigate characterization performance. In the first experiment, all six models were applied to the colour samples of the IT8 chart and colour samples of PCC, respectively, to understand the modeling accuracy in terms of the degree of polynomial. For the IT8 chart, all colour samples (264) were used to derive the model. For PCC colour samples, 100 evenly spaced colour samples were chosen at 10 different hue angles (i.e., neutral, 18°, 45°, 81°, 126°, 162°, 198°, 234°, 288°, and 324°). Both 8-bit and 12-bit camera RGB values were used to capture IT8 colour samples. The results were used to investigate the accuracy of colorimetric mapping with respect to the quantization level of the pixels' RGB values.

For practical camera characterization, it is essential to understand the generalization of the model derived. That is, would the matrices derived by colour samples of a training set fit those colours that are not represented in the training. Theoretically, a matrix derived by a training set with more colour samples would be more general for all the colours within its colour gamut. However, in practice it is preferable to use only a few training samples to minimize time and effort. The second experiment investigates the accuracy of the matrices derived when different numbers of training samples were used. In this experiment, only the 3×11 matrix was applied for characterization using colour samples from the IT8 chart. The numbers of selected colour samples were 96, 60, 42, 33, and 24. A set of 168 colour samples was used to test the performance of each matrix derived by a different number of training samples.

EYE–CAMERA METAMERISM

When two colours having a different spectral composition visually match one another under one set of conditions, they are said to be metameric and the phenomenon is referred to as metamerism.[14,15] Usually, different reflectance curves result in different observed colours. However, the eye responds to light not on a wavelength-by-wavelength basis, but as a result of integrating the colour responses across the visible spectrum, and so certain colours with different reflectance curves can appear similar in a particular viewing condition. In terms of colour measurements, metamerism is defined when two colour samples have the same tristimulus values for a specific combination of illuminant and observer, but the reflectance curves are different.

For camera characterization, metamerism poses a tremendous challenge. As mentioned earlier, because the spectral responses of the RGB sensors of a camera are different from the CIE colour-matching functions, the camera system "sees" colours differently from those perceived by human eyes, and vice versa. For example, colours that are

metameric with respect to human eyes need not be metameric with respect to camera sensors. Two metameric colour samples Q_1 and Q_2 matching each other under a given illumination for human eyes can be expressed as

$$\begin{aligned}
\int S(\lambda)R_1(\lambda)\bar{x}(\lambda)d\lambda &= \int S(\lambda)R_2(\lambda)\bar{x}(\lambda)d\lambda \\
\int S(\lambda)R_1(\lambda)\bar{y}(\lambda)d\lambda &= \int S(\lambda)R_2(\lambda)\bar{y}(\lambda)d\lambda \qquad (4) \\
\int S(\lambda)R_1(\lambda)\bar{z}(\lambda)d\lambda &= \int S(\lambda)R_2(\lambda)\bar{z}(\lambda)d\lambda,
\end{aligned}$$

where $R_1(\lambda)$ and $R_2(\lambda)$ are the spectral reflectance of Q_1 and Q_2, respectively, $S(\lambda)$ is the spectral power distribution of the illuminant, and $\bar{x}(\lambda)$, $\bar{y}(\lambda)$, $\bar{z}(\lambda)$ are CIE standard colour-matching functions. It is clear that, under the same lighting condition, changing the observer to one characterized by a different set of colour-matching functions, in general, results in a colour mismatch between the two given colour stimuli. That is,

$$\begin{aligned}
\int S(\lambda)R_1(\lambda)\bar{r}(\lambda)d\lambda &\neq \int S(\lambda)R_2(\lambda)\bar{r}(\lambda)d\lambda \\
\int S(\lambda)R_1(\lambda)\bar{g}(\lambda)d\lambda &\neq \int S(\lambda)R_2(\lambda)\bar{g}(\lambda)d\lambda \qquad (5) \\
\int S(\lambda)R_1(\lambda)\bar{b}(\lambda)d\lambda &\neq \int S(\lambda)R_2(\lambda)\bar{b}(\lambda)d\lambda,
\end{aligned}$$

where $\bar{r}$, $\bar{g}$, $\bar{b}$ represent the spectral sensitivity of each R, G, B channel of the camera.

The magnitude of the colour mismatch is directly related to the magnitude of the differences between the spectral reflectance, defined by $R_1(\lambda)d\lambda$ and $R_2(\lambda)d\lambda$, of the two given colour samples under a specific illumination. Thus, a camera may generate two different sets of RGB values at two colour samples, while to human eyes they look the same. This failure to agree on this kind of colour match is termed eye–camera metamerism. The consequence of this for camera characterization is that the transfer matrices derived are material dependent. That is, the transfer matrix derived from colour samples of one material achieves its best performance only when it is used for predicting colour samples from the same material. For colour samples made of another material or produced using a different set of colorants, the modeling accuracy is generally much worse. The reason for this is that, when two colours on two different media have the same CIE tristimulus values (i.e., metameric to human eyes), the RGB values generated by the camera are often different. Consequently, their transfer matrices derived by polynomial regression are necessarily different.

It is desirable that one reference target can be used to characterize the camera for colour samples of any material for practical reasons. To investigate this eye–camera metamerism effect, two experiments were carried out. In the first experiment, a matrix derived from one particular set of surface reflectance is used to predict other sets of surface reflectance, providing an estimation of metamerism between two materials "seen" by the camera vs. human eyes in terms of colour difference. Assume that there exist two sets of colour samples, each with different spectral composition but "seen" to be the same by the camera (having the same camera RGB responses) under a given illumination. As mentioned earlier, once the "observer" is changed from camera to CIE standard observer, there is a colour difference between the colour samples. And this colour difference can be considered as the degree of observer metamerism between these two materials.

In practice, it is extremely difficult to get the camera RGB values and their corresponding *XYZ* values of two sets of real, but metameric, colour samples, which are "matched" by a camera, i.e., $RGB_1 = RGB_2$ and $XYZ_1 \neq XYZ_2$. In the experiment, a 3×11 transfer matrix for IT8 colour samples was first derived using its own colour samples. Suppose that there exists a set of IT8 colour samples that have the same RGB values as colour samples from PCC, i.e., they look identical to the camera under the same lighting condition. As explained, due to this eye–camera metamerism, they look different to human eyes, i.e., their *XYZ* values are different. For PCC colour patches, they can be measured to obtain their *XYZ* values. For the supposed IT8 colour patches, their *XYZ* values can be approximated with the transfer matrix derived by characterization. Two different sets of *XYZ* values are now available for metameric colour samples that have the same camera RGB responses. Thus, the averaged colour difference between these two sets at a given illuminant can be calculated.

In addition to the colour samples from IT8 and PCC, a Macbeth ColorChecker was also used in the experiment. The degree of metamerism between an IT8 chart and Macbeth ColorChecker is also calculated for comparing with the degree of metamerism between the IT8 chart and PCC textile samples.

The second experiment intended to answer the question of whether using more terms in the transfer matrices would reduce this eye–camera metamerism when a matrix derived by colours of one media is used to predict colours of another media. In other words, would more terms in the transfer matrices bring about better performance for cross-media prediction. In this experiment, matrices of 3×3, 3×5, and 3×11 were used for comparing the results.

RESULTS AND DISCUSSION

Characterization by Different Sizes of Matrices

Tables II and III show the results obtained for the IT8 chart and PCC textile samples, respectively, by various sizes of transfer matrices when RGB values are quantized to 8 bits. The distributions of the prediction errors generated by each matrix were shown in Figs. 2 and 3. The aim is to

TABLE II. Model performance by various polynomials for IT8 (8-bit RGB data).

Matrices	Average ΔE	Maximum ΔE
3×3	2.48	14.6
3×5	1.67	9.1
3×6	1.80	12.8
3×8	1.50	8.5
3×9	1.54	13.3
3×11	1.07	6.7

discover the connection between modeling accuracy and the number of terms used in the matrices. As expected, the matrix with 3×11 terms produces the best results for both IT8 chart and PCC textile samples with an average colour difference, ΔE, of around 1 CMC(1:1) unit. All ΔE values refer to CMC(1:1) hereafter.

It is generally believed that more terms in a matrix produce better results. However, the results from this study show that this is not always the case. Predictive accuracy actually depends on the particular terms used. It seems that the terms *rgb* and 1 play a significant role in reducing both the average ΔE and maximum ΔE, especially when fewer terms were adopted. For example, adding *rgb* and 1 to the simplest 3×3 linear matrix actually makes it out-perform 3×6 and 3×9 matrices.

To find the link between prediction errors and different colour attributes, ΔE vs. lightness (L^*), ΔE vs. chroma (C^*), and ΔE vs. hue angle (h) are plotted in Figs. 4 and 5, respectively. The results were obtained when a 3×11 matrix was used. Figure 4(a) clearly shows that colour samples with high lightness can be predicted more accurately than those with low lightness. The largest colour differences are produced by those very dark neutral colours (lightness less than 10). Some possible reasons for this phenomenon are:

1. The transformation matrices were generated by least squares fitting camera RGB values to *XYZ* values. Therefore, the prediction errors are evenly distributed throughout *XYZ* colour space. However, because of the use of cubic-roots in the transformation from *XYZ* to CIELAB, the same difference in *XYZ* colour space would not remain proportionally the same in CIELAB colour space. Thus, the perceived colour difference increases as *XYZ* values decrease.
2. The RGB signals generated by the camera have a lower signal-to-noise ratio when their responses are very low. This means that the signals are less accurate (or noisier) for dark sample.
3. Spectrophotometers generally become less accurate when the lightness level of the colour measured becomes very low for the same reason as the camera. Therefore, those large errors might be a combination of the inaccuracy of both instruments at the dark end.

TABLE III. Model performance by various polynomials for PCC (8-bit RGB data).

Matrices	Average ΔE	Maximum ΔE
3×3	3.11	13.4
3×5	1.40	4.5
3×6	2.29	11.4
3×8	1.33	4.8
3×9	1.33	11.5
3×11	0.97	3.7

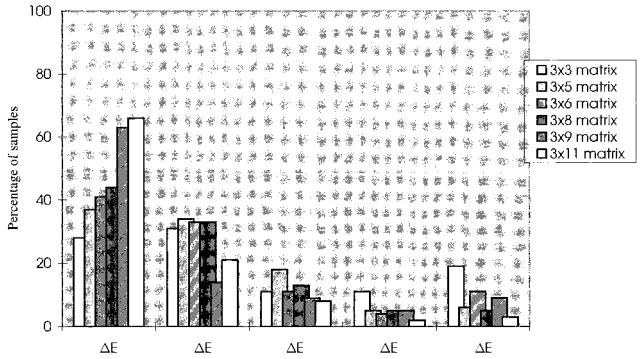

FIG. 2. Distribution of colour differences by various polynomials (IT8).

Figures 4(b) and 5(b) show again that predictions for neutral colours are less accurate. Figures 4(c) and 5(c) show that there is no clear relationship between ΔE and hue angle (excluding neutral colours). In other words, the predictive performance of the model is consistent for all hue angles. However, it should be pointed out that those dark, highly saturated colours are also less accurately predicted.

It seems that the modeling performance for PCC is better than IT8, especially in terms of maximum ΔE. However, in comparing the lightness values of colour samples from IT8 and PCC, it can be seen that the darkest colour samples contained by PCC were around 20 in lightness, while IT8 contains quite a few colour samples whose lightness level is well below 15. Those very dark colour samples produce large ΔE values.

Characterization with Different Levels of Quantization

Table IV shows the results obtained for the IT8 chart by various sizes of transfer matrices when camera RGB values are quantized to 12 bits. The results show that the improve-

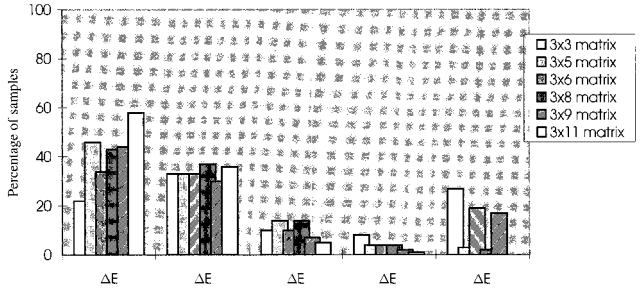

FIG. 3. Distribution of colour differences by various polynomials (PCC).

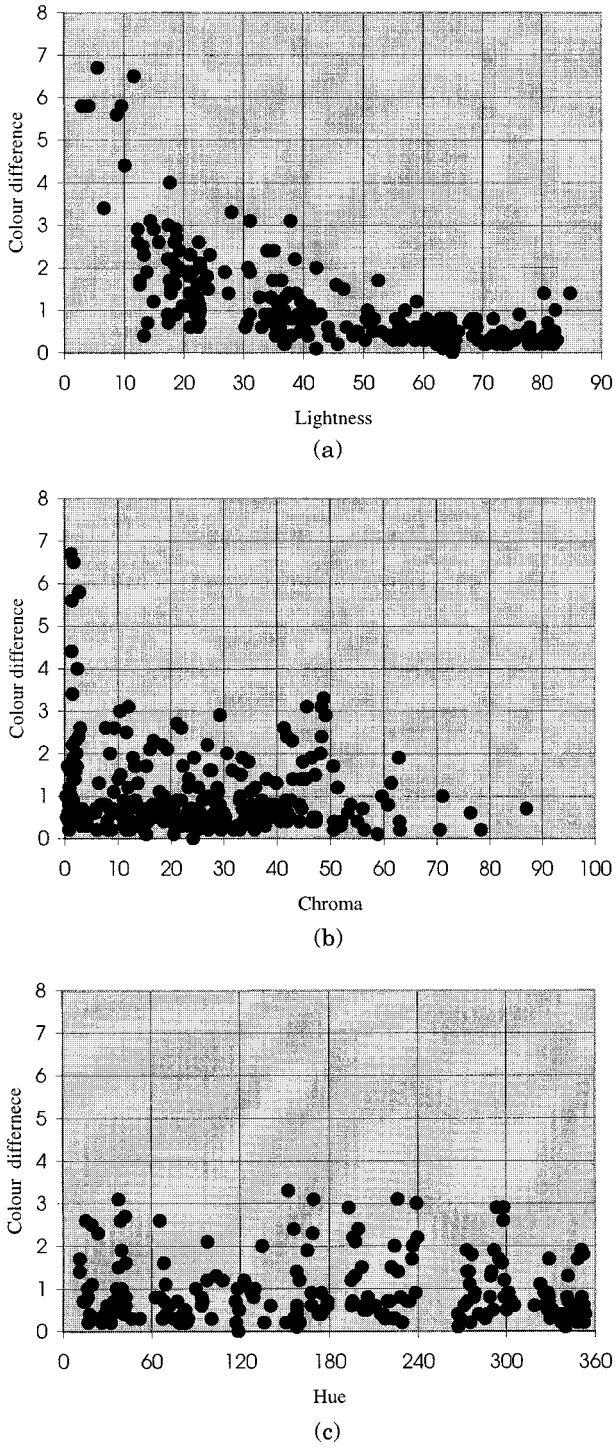

FIG. 4. Results of IT8 by 3 × 11 matrix: (a) plot of lightness vs. ΔE; (b) plot of chroma vs. ΔE; (c) plot of hue angles vs. ΔE (excluding neutral colours).

ment over 8-bit data is trivial in both average ΔE and maximum ΔE. Bit depths of RGB values (8 or 12) for this camera do not make much difference, i.e., there is minimal quantization error. This could be because the discarded 4 bits contain mostly noise; however, this does not mean that an 8-bit camera yields similar results. What matters is not just the number of bits, but also the signal-to-noise ratio. The use of the averaged RGB values of each colour patch helped to improve the accuracy of the 8-bit data. Although each individual 8-bit pixel is less accurate than the 12-bit pixel, the accuracy of averaged RGB values in 12 bits would be only slightly better than averaged RGB values in 8 bits, if the noise distribution of 8-bit data were symmetrical about zero.

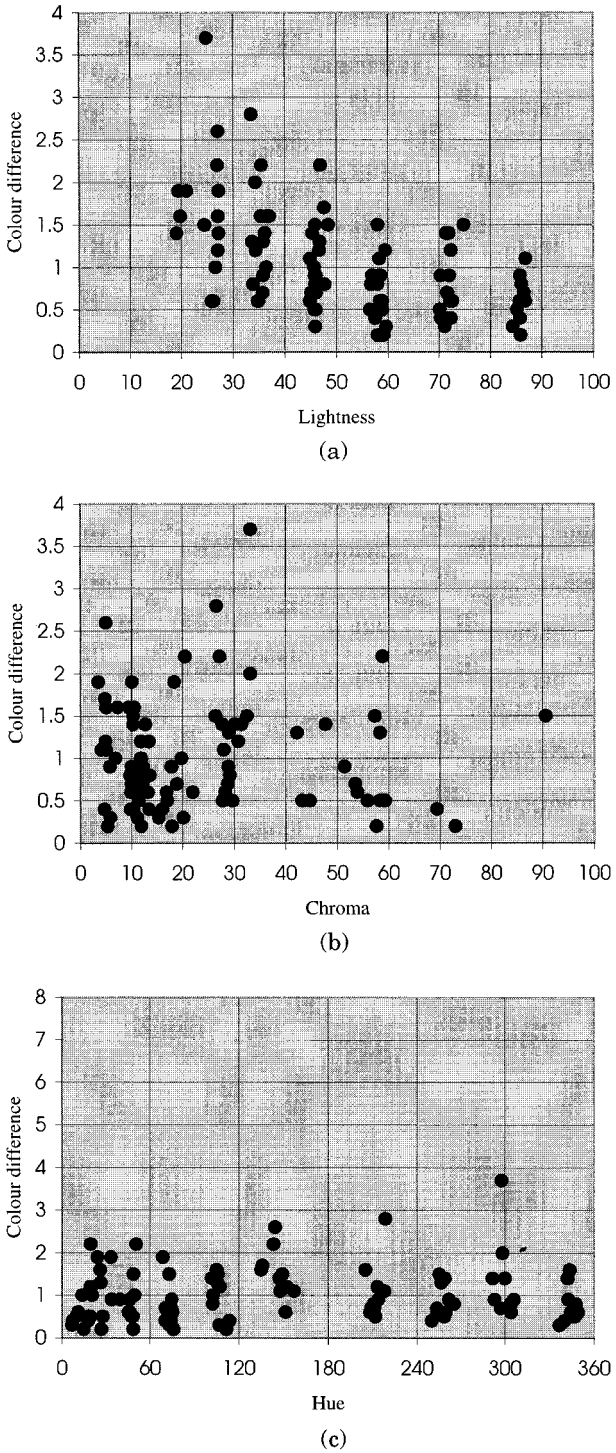

FIG. 5. Results of PCC by 3 × 11 matrix: (a) plot of lightness vs. ΔE; (b) plot of chroma versus ΔE; (c) plot of hue angles vs. ΔE (excluding neutral colours).

TABLE IV. Model performance by various polynomials for IT8 (12-bit RGB data).

Matrices	Average ΔE	Maximum ΔE
3×3	2.47	14.2
3×5	1.56	6.8
3×6	1.79	12.2
3×8	1.41	6.4
3×9	1.53	12.8
3×11	0.98	7.3

TABLE VI. Results of cross-media eye-camera metamerism.

	Metamerism		
Material	3×3	3×5	3×11
IT8 → IT8	2.48	1.67	1.07
IT8 → PCC	4.67	4.43	3.97
IT8 → Macbeth ColorChecker	3.24	2.96	2.60

Characterization by Different Numbers of Training Samples

Table V gives the results obtained when different numbers of training samples were used to derive the model. The total average ΔE increases by about 0.7 units between the models derived by 96-sample and 24-sample training sets, when the model was applied to the same testing set. The maximum ΔE increases by about 5 ΔE units. It can be seen that modeling accuracy does not improve significantly when the number of training samples is over 60. As expected, the generalization of the matrices derived improves as the number of training samples increases. This is shown by the consistent decrease in the average colour difference, when the derived matrix was applied to the same testing samples.

Eye–Camera Metamerism

Table VI shows the degree of metamerism calculated between IT8 chart samples, PCC colour samples, and Macbeth ColorChecker samples using camera RGB data. The degree of observer metamerism between IT8 and PCC is around 4 ΔE units. The degree of observer metamerism between IT8 chart and Macbeth ColorChecker is around 2.6 ΔE units under the same conditions. It should be noted that, according to earlier experimental results, the derived characterization model itself has an average prediction error of about 1 ΔE unit. The matrix derived using IT8 gives a better prediction for Macbeth ColorChecker chart than for PCC textile samples. This is most likely due to the fact that the spectral differences between IT8 and Macbeth ColorChecker are less than those between IT8 and PCC. Table VI also shows the results of predictive performance when matrices of 3×3, 3×5, and 3×11 were used. It is clear that, because of the existence of this eye–camera metamerism, the transfer matrices derived by colour samples from one particular set of targets or dyes do not produce the same accuracy when they are used for predicting colour samples of another material. Although using more terms in the transfer matrix brings about some improvement, the improvement is much less significant compared with the improvement when only one medium is involved. This means, for cross-media camera characterization, that the number of terms in the polynomials has little impact on metamerism. From this study, a typical performance of about 2–4 ΔE units is obtained by using 3×11 transfer matrices. This level of accuracy may satisfy some colour-reproduction applications that do not require very high colour fidelity. However, for applications that require the complete elimination of this metamerism, a solution lies in multi-spectral imaging,[16] where the camera response RGB data can be used to achieve an approximation of the spectral reflectance of the colour being pictured. Once the spectral reflectance of the colour is obtained, its XYZ values can be calculated.

CONCLUSION

This paper article describes a method for establishing a relationship between a commercial digital camera's RGB responses and CIE colorimetric values. Modeling accuracy with an average 1 CMC(1:1) ΔE unit is typical, when a 3×11 matrix is used. The black "l" and white "rgb" terms seem to be very important, especially when a small number of terms is used. The generalization of the model derived improves as the number of training samples increases. To achieve a reasonable accuracy of prediction, 40–60 training samples seem to be a suitable number, and there is a limit to the improvement in accuracy made by additional samples. Choice of characterization target and media, and their effect on metamerism have been examined. It is demonstrated that a model is dependent upon both media and colorant, and applying a model to other media/colorants can lead to serious eye–camera metamerism problems. This has particular implications for cross-media colour reproduction.

TABLE V. Model performance (3×11 matrix) for training samples and testing samples.

Training samples	Testing samples	Av. ΔE training	Max. ΔE training	Av. ΔE testing	Max. ΔE testing
96	168	1.21	7.4	1.16	7.1
60	168	1.21	6.7	1.16	6.3
42	168	1.32	6.0	1.28	7.5
33	168	1.24	5.6	1.50	10.4
24	168	1.25	5.1	1.85	12.1

ACKNOWLEDGMENTS

The authors thank Dr. Ján Morovic and Dr. Graham Finlayson for their discussion and constructive suggestions for this work.

1. CIE Pub. 15.2, Colorimetry. 2nd Ed. Vienna: CIE Central Bureau; 1986.
2. ISO 17321 WD 4, Colour characterisation of digital still cameras using colour targets and spectral illumination; 1999.
3. Berns RS, Shyu MJ. Colorimetric characterisation of a desk-top drum scanner using a spectral model. J Electronic Imag 1995;4:360–372.
4. Hung PC. Colorimetric calibration in electronic imaging devices using a look-up table model and interpolations. J Electronic Imag 1993;2:53–61.
5. Hung PC. Colorimetric calibration for scanners and media. Proc SPIE 1991;1448:164–174.
6. Kang HR. Colour scanner calibration. J Imaging Sci Tech 1992;36: 162–170.
7. Kang HR, Anderson PG. Neural network applications to the colour scanner and printer calibrations. J Electronic Imag 1992;1:125–134.
8. The ANSI Accredited Standards Committee IT8.
9. Park J, Park K. Professional colour communicator—the definitive colour selector. J Soc Dyer Colour 1995;111:56–57.
10. Clarke FJJ, McDonald R, Rigg B. Modification to the JPC79 colour-difference formula. J Soc Dyer Colour 1984;100:128–132.
11. Hunt RWG. Measuring colour. 2nd Ed. London: Ellis Horwood; 1995.
12. Johnson T. Methods for characterising colour scanners and digital cameras. Displays 1996;16:183–191.
13. Kang HR. Colour technology for electronic imaging devices. SPIE; 1997.
14. Wandell BA. Colour rendering of colour camera data. Color Res Appl 1986;11:S30–S33.
15. Lee RL. Colorimetric calibration of a video digitizing system: Algorithm and applications. Color Res Appl 1988;13:181–186.
16. Konig F, Praefcke W. A multispectral scanner. Proc Colour Imag Multimedia Conf 1998. p 63–73.

View publication stats